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The Role of AI in Tailoring Treatment Plans for Patients

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ABSTRACT

Artificial Intelligence (AI) is transforming modern medicine by enabling the development of personalized treatment plans tailored to individual patients' genomic, physiological, and behavioral data. With increasing access to large-scale biomedical datasets and advanced deep learning techniques, AI plays a central role in precision medicine by enhancing drug discovery, optimizing treatment schedules, and matching therapies to patient-specific profiles. This paper explores the historical evolution, current applications, and future potential of AI in clinical decision-making, particularly in oncology and neuroscience. Key AI technologies, such as machine learning, deep learning, and natural language processing, are examined in the context of their roles in diagnostics, treatment planning, and patient monitoring. Despite promising results, challenges such as algorithmic bias, data privacy, regulatory barriers, and the interpretability of AI-driven decisions continue to limit their full integration into clinical practice. The study highlights the importance of transparency, collaboration, and ethical oversight in advancing AI-driven healthcare solutions that are inclusive, reliable, and equitable.

Keywords: Artificial Intelligence (AI), Personalized Medicine, Deep Learning, Machine Learning, Clinical Decision Support, Precision Medicine.

INTRODUCTION

With substantial advances in recent years, Artificial Intelligence (AI) models for data interpretation utilizing deep learning solutions have been assessed in numerous biomedically relevant applications. These include medical imaging systems for disease screening and management, precision medicine (PM) solutions for matching patients with targeted drugs tailored to their specific genomic/genetic alterations, and gene and genetic variant prioritization pipelines. Encouraging initial demonstrations of success and feasibility for all three types of AI solutions have been published. In the context of PM, recent efforts to deploy AI solutions encompassing a broad range of several critical areas, including drug discovery and development, targeted (anti-)cancer drug prediction, repurposing existing drugs, treatment scheduling and dose optimization, and pairing patients with combination treatment plans, particularly chemotherapy and immunotherapy have shown promise. However, as the AI-based treatment solutions reach technological maturity, their clinical implementation may be impeded by challenges and concerns associated with various technology-driven, methodological, and ethical issues. These challenges relate to both primary AI and medical issues affecting day-to-day operations and usage effectiveness in a real-world clinical setting. For their development, evaluation, and deployment, AI systems should ensure transparency, accountability, and interpretability of data input sources and flow chart steps for user feedback, scrutiny, and trust. A recent analysis of an AI-based radio-therapy regimen generator for prostate cancer presented promising results for its clinical applicability. A typical patient treatment plan

generated consisted of a median of 866 control points, and 89% of the plans generated were deemed clinically acceptable [1, 2].

Understanding AI in Healthcare

IIn recent years, artificial intelligence (AI) has gained prominence in precision medicine (PM) due to its ability to efficiently process large multi-omics data. PM approaches typically consider tissue, blood, and imaging biomarkers, along with polygenic risk scores, to tailor treatment plans for patients. However, successfully implementing these approaches involves extensive data engineering and integrating various biomarkers to predict treatment responses, all of which have become increasingly complex due to the rise of multi-omics methodologies that analyze diverse biological data. This complexity has made neuroscience PM approaches challenging to apply in practice. Though the foundational studies focus on several key areas, the AI techniques explored usually reflect how these studies were conducted. AI is often seen as an interdisciplinary umbrella encompassing various sub-disciplines, making it difficult to define precisely. Many PM researchers, primarily consisting of physicians and biomedical engineers, often lack in-depth AI knowledge, which limits their ability to leverage AI's potential. Over recent decades, there has been growing interest in applying AI to healthcare-related challenges. As biomedical data volumes surge, understanding AI's role as a crucial technology to manage this influx is vital. This review will discuss both algorithmic and non-algorithmic AI and summarize current anticipated use cases in healthcare with specific examples. It aims to provide a comprehensive overview for researchers interested in using AI to address healthcare issues and serve as a reference for healthcare leaders seeking insights into AI's contributions to their organizations [3, 4].

Definition of AI

Artificial intelligence (AI) encompasses systems that emulate human cognitive functions and behaviour to resolve problems, amplify productivity, foster innovation, and facilitate novel solutions. The development of AI has spurred global interest as well as concerns among governments, corporations, and citizens regarding its efficacy and security. A subset of AI is machine learning (ML), wherein the system learns from input data to yield predictions or estimates. ML entails various approaches, with deep learning (DL) being a high-performing implementation of ML. Devices developed using deep learning employ multilayered networks of mathematical functions to glean autonomous features from inputs while continuously refining their parameters for optimal prediction. It thus functions more like a human brain than traditional computation models. AI's growing use in enhancing productivity across diverse sectors has propelled interest and investment in its medical applications, as it holds the promise of improving disease understanding and management with far-reaching effects on patient treatment and remedy accessibility. The clinical approach has entered the big data era, owing to the expanse of physiologic measurements, health data, and genomic information with diverse temporal and geographical scales, which have fueled the growth of biomedical data sciences. Machine learning (ML) and deep learning (DL), AI technologies with improved scalability and versatility for data processing, notification, pattern recognition, simulation, and decision assistance, can be trained on these data sources to improve health understanding and management. However, the absence of appropriate platforms and clinical trial designs is hindering the implementation of recent translational advances of AI to practice. Despite the rapid rise of this brand new field, many basic questions are yet to be answered, such as whether the amalgamation of datasets, platforms, methods, and knowledge from multiple domains to develop AI technologies can benefit health care. And if so, what are the required preconditions, designs, and regulations? Will AI-aided diagnostics and treatments be able to stand against or even enhance human understandings and decision-making? [5, 6].

History of AI in Medicine

Artificial intelligence (AI) has been available in rudimentary forms for many decades. Simple expert systems were first described in the 1970s, and clinical decision support tools are a form of AI that has also been available for decades. However, AI methods had little practical impact on the practice of medicine for many decades. Beginning around 2012, AI has, however, emerged as an increasingly important tool in healthcare. This is evident from the sharp increase in publication numbers in this field, as well as the recent approval of AI-based devices for clinical use. These devices are now capable of processing image data, making diagnoses, predicting biomarkers for solid tumors, and more 7. However, the development of AI in medicine is still in its infancy. While many AI-based devices have recently been introduced to the market, most literature still derives from early prototypes or methods that have not found translation into

mainstream clinical practice. Additionally, since 2022 there have been exponential technical advancements in AI, with some AI programs now demonstrating human-level understanding of image and text data. The idea of machines emulating human cognition dates back to antiquity. However, the field of AI arose in earnest as an academic discipline in the 1950s when NASA coined the term. In the 1960s and 1970s, the first rudimentary AI systems, often based on rules or decision trees, were described. Early successes led to overconfidence and unrealistic expectations so that the field faced reduced funding and diminished interest during the so-called "AI Winter" in the late 20th century. There were successful ideas from AI such as expert systems found applications in healthcare or financial domains but with limited impact. The introduction of deep learning and the availability of graphics processing units (GPUs) for demanding computations led to massive advancements in AI since 2012. This newly found power was quickly adopted by the tech industry, and today the majority of newly available AI methods are designed for and applied in private sector domains such as technology, insurance, finance, or logistics [8, 9].

Personalized Medicine

Personalized medicine originates from specialized medicine and is a dynamic process involving intrinsic knowledge about a patient's treatment response, considering pharmacokinetic and pharmacodynamic parameters. Treatment plans are continuously modulated based on individual responses, prior treatment complexity, and defined criteria. Cancer therapies rarely succeed uniformly across all patients, necessitating treatment modulation when heterogeneous responses are detected. This shift from a narrow view of disease classification to a universal carcinogenic perspective allows for a more individualized treatment approach, leading to hyper-personalized interventions. The prescription of medications can be enhanced with artificial intelligence (AI) using individual patient data. AI aids in formulating hypotheses, identifying risk factors, and assisting in trial designs through simulation and drug screening workflows focused on single cases rather than population data. AI clinical trials consist of calibration and efficacy-driven phases. Calibration trials aim to establish dose modulation methods supported by predictive models, engineering patient-specific clinical trials while minimizing population learning, ensuring attention remains on the individual patient [10, 11].

AI Technologies In Treatment Planning

Few recent advancements show more promise in the oncological field than artificial intelligence. The ability of machines to work through the vast amounts of medical documents to find new insights goes well beyond human capabilities. New treatment techniques that were developed from guidelines or literature research can be integrated to AI systems or planning software, and all known cognitive algorithms can be used to generate a treatment plan. However, the additional workload of using review systems, and the knowledge of the treatment planning process still needed for statistical treatment plan generation, are major barriers for facilities to start using machine learning systems in clinical practice, similar to most machine learning systems. In most countries, reimbursement and hospital budgets are tight. Plans generated by AI can provide the treating physician with additional knowledge and expertise on top of the plans generated by manual planning. Additionally, AI can be used as a first reviewer to create real-time benefit-risk ratios and plausibly optimal treatment plans on which the treatment planner can base the final product. Most of the countries have restrictions on using third-party software: they are often illegible for reimbursement and have limited guided workflows and development options. A vendor-neutral solution required the creation of an extensive responsive user interface and plan review interfaces. Each review step lacked guidelines like the one that guided user insight into treatment plans in the first visit. The need for a foundation review plan that provides the reviewers with a review that goes beyond just safety aspects cautions against any button being found sufficient. But careful fielding of these plans to the clinical users should greatly complement the plans already reviewed by consistent and explanatory comments and provide further insights into planning objectives and which modalities could prospectively treat better [12, 13].

Data Sources for AI Algorithms

The development, validation, and implementation of AI algorithms occur within a cyclical process that considers a range of issues, beginning with a business problem and concluding with the deployment of an algorithm into the healthcare system. AI algorithms operate as an identification tool that interprets the inputs seen during training. The vast majority of imaging data employed during development may take the form of 2D images and volumetric (3D) data, with a wide range of formats. To deploy deep learning algorithms into a health information system requires interoperability with a resource-constrained,

heterogeneous environment, thus necessitating pre-processing of the input data. Both domain knowledge and appropriate engineering resources are critical to the success of the deployment phase. Improvements in the detection capabilities of AI algorithms typically rely on the effort put into the preprocessing phase. As a direct takeaway, state-of-the-art AI algorithms rely on a lot of development effort on a wide range of pre-processing techniques that, when not present in a production setting, can result in a significant performance drop. Moreover, the production-ready algorithms considered in this paper are based on commercial AI packages that allow for the implementation of the models by end-users with limited programming experience. Since these commercial approaches are closed, there are obvious concerns about technological obsolescence and product life cycle. Therefore, companies and institutions investing in this technology should consider the risks involved in the sustainability of the solutions developed as well as the requisite activity needed to transition from the currently accessible development packages into self-managed deployment-ready solutions. However, the majority of AI algorithms targeting long-term utilization are either in the multiinstitution evaluation phase or remain as clinical proof-of-concept studies. Consequently, although less connection-focused algorithms have been developed and are now gaining traction within hospitals internationally, the majority of commercial efforts focus on algorithms combining both 3D and 2D information. These algorithms must be trained on larger and more various data repositories, thus raising the need for ongoing research cooperation and investment [14, 15].

AI-Driven Decision Support Systems

The advent of internet-enabled devices has facilitated the emergence of vast amounts of health-related data, ranging from deep unstructured data from electrocardiogram or histopathology images to semi-structured data, such as voice and text transcripts of doctor-patient conversations and free-text reports on patients' conditions. This influx of information streams has the ability to revolutionise patient care and enhance the quality of healthcare delivery. However, the increasing volume serves as a looming threat to healthcare professionals, who confront a tidal wave of unmanageable data streams daily, leading to missed opportunities and oversights in patient care. Advanced technologies that manage health-related content already exist, but providing these technologies with the necessary healthcare knowledge and clinical reasoning required to solve clinical problems is challenging. This gap between vast amounts of useful data and tangible knowledge has rendered already available tools ineffective, necessitating the development of more sophisticated technologies capable of bridging the gap. This creates an opportunity for intelligent means possessing reasoning capabilities. AI has the potential to address this challenge by using a variety of technologies, including ones capable of using both qualitative and quantitative knowledge. Identification and intelligent extraction of the patient's picture of the world/psychological state are covered; and, most importantly, intelligent decision-making procedures for personalized adaptive treatments to care. All these AI technologies act in synergy with one another. For instance, using sentiment analysis on recorded doctor-patient conversations helps extract the state of distress, laden with qualitative uncertainty. If a high degree of patient dissatisfaction arises from the sentiment analysis, a logical reasoning approach to diagnosis could be triggered to infer the cause of that dissatisfaction. This approach explains the rationale behind the generated treatment plan. Reasoning capabilities grounded on ontologies could be fed into fuzzy AI systems to create healthcare outcomes expressed in natural language that could be easily understood by patients [16, 17].

Challenges In Implementing AI

Despite the emerging role of AI in identifying suitable treatment plans, challenges remain in implementing them in clinical practice. The conventional approach to drug development and repurposing requires applying for new drug applications (NDA) after conducting safety and efficacy studies based on clinical trial phases I, II, III, and IV. The lack of certainty in AI drug repurposing further complicates the enactment of drug repurposing texts developed by AI. Technically, AI devices and techniques are still in their infancy in drug repurposing. Most drug repurposing methods are not novel and only use traditional approaches. Moreover, most AI techniques relevant for drug repurposing do not lend themselves to easily interpretable decision insights or explanations. It is difficult for specialized professionals to comprehend, evaluate, and validate drug repurposing decisions rendered by such black-box AI tools. Another critical challenge is related to biased and data privacy concerns. Only a few companies make their datasets publicly available for research. Moreover, most proprietary datasets do not contain information on ethnicities, which is vital for health disparities research. Access to such data is often limited to projects draped in confidentiality clauses, resulting in biased datasets that fail to reflect the full spectrum of the

target population. Furthermore, most protected health information (PHI) must be de-identified to protect privacy, further complicating dataset accessibility. The black-box nature of some AI algorithms invites claims about lack of trust in AI systems and difficulties regarding liability and accountability if something goes wrong. The lack of transparency, reliability, and faithfulness in the insights generated by AI systems fuels distrust, while questions about the sovereignty and accountability of AI systems arise. These challenges must be adequately addressed to facilitate the broader adoption of AI [18, 19].

Case Studies

Clinical medicine is an area closely related to traditional medicine that is benefitting greatly from big data, machine learning, and AI. From 1990-2019, publications pertaining to AI in clinical medicine increased from less than 50 to over 1,350. The majority of these papers focus on the analysis of clinical imaging and pathology data to assist the diagnostic processes. Similar to the genomics field, much of the AI work in clinical medicine is centered around refining outputs generated by existing methods. Among dozens of identified AI approaches for repositioning anti-cancer compounds, the most advanced models are ensemble methods combining multiple approaches. In a blinded collaboration with a pharmaceutical partner, the methods successfully identified a follow-up cancer drug with human activities within the top four compounds predicted to be active, out of over 4,000 tested. Chemoinformatics approaches dissected structural information from a library of drugs, while machine learning models assisted in the selection of prospective compounds across major target families. Experimental testing confirmed the predicted re-purposing of a number of anti-cancer compounds. As evidence accumulates regarding the associations between drug side-effects and other biological properties for drug candidates, these data can also assist in the discovery of new uses for existing drugs. An EU-funded project focusing on repositioning compounds for repurposing as a therapy for Alzheimer's disease developed an approach utilizing chemical and biological data combined with association information from the literature. The objective of the approach was to generate and prioritize compound candidates screened from commercial ready-to-test libraries. The approach successfully identified compounds that impinge on different biological targets. Here, association information from multiple information sources including literature-based, gene-related, side-effect-related were utilized [20, 21].

Future Directions

AI-driven models have shown promising applicability in precision medicine but must address numerous challenges before they surpass conventional approaches. There is a pressing need for additional rigorous validation studies on the detection and interpretation of molecular biomarkers based on AI approaches. Application of resources on the development of tools for open-access comparison among state-of-the-art models and consequently selection of the optimal model to be utilized in a given setting is warranted. It is highly desirable to establish libraries of AI-generated drugs to ensure novelties in potential treatment options, which may also facilitate drug repurposing. The rapid evolution and proliferation of AI tools and pipelines to aid in preclinical drug research has spawned a paradigm shift for research and clinical communities. However, despite their enormous potential, potential users should remain cautious against excessive marketing claims of AI tool developers and vendors, and striking a balance between hot-spot innovations and established, conventional techniques should be needed to maximize the utility of resources. Most importantly, regulation and legislation should keep pace with the vast changes introduced by the adoption of AI. Granting certain hallmarks of citizenships could foster responsible development and deployment of AI, while the setting up of global standards for tools, numerical data, and interpretability protocols would facilitate comprehensive reviewing of algorithms [22, 23].

Ethical Considerations

The role of AI in treatment planning should feature minimal automation, with doctors leading decision-making. AI can assist but should not take over. Using non-small cell lung cancer patients as an example, it highlights the trade-offs between forecasting treatment outcomes with AI versus traditional methods. The goal is to align new medical decisions with existing decision theories, resembling feature extraction in supervised learning rather than policy transfer in reinforcement learning, as forecasting relies on pattern similarity. Heuristics often govern decision-making; non-experts may struggle with decision theory, while experts might only approximate correctness. Intuitive forecasting techniques like scenario planning can aid policy-making despite uncertain logic. Doctors should blend their insights with AI predictions, evaluating personal medical evidence and interpreting AI forecasts through their knowledge and ethics. This would combine empirical reasoning with fairness principles, enhancing AI transparency

and patient involvement. Medical decisions should remain rooted in doctors' judgment over AI outputs. A comprehensive response requires a true representation of reality, including facts and decision criteria. In machine ethics, AI alignment with human values is crucial; misalignment would yield optimal decisions for the AI itself rather than humanity. Value alignment, in tandem with uncertainty reasoning and model fidelity, represents another key dimension of the first H2 question. AI safety is typically framed around three main concerns: unintended misuse, undesired side effects, and control issues [24, 25].

Patient Perspectives

Incorporating perspectives from patients with implantable cardioverter defibrillators (ICDs), this study highlights concerns regarding future developments in the use of AI technology for risk stratification and treatment planning in SCD (sudden cardiac death) prevention. Given the highly personal implications of implanting an ICD, patients desire decision-making that takes into account human experiences and emotions. AI-driven decisions may jeopardize this. In general, incorporating observational, real-world, and unstructured data may lessen the need for and accessibility of specialist knowledge, altering the dynamics of the patient-doctor relationship. Although AI has noteworthy advantages, purpose and design will determine its ethical and societal acceptability. In the present context, addressing conditions in which implementing the same ML algorithm has different effects is equally relevant for those involved in the development of personalized medicine, such as AI-based disease risk stratification and treatment planning. Whereas patients unanimously viewed data-driven protocolization of work processes with great skepticism, in parts of this, a proper and careful implementation of the notion of developing AI-based personalized medicine was welcomed. Given the intentions and interests involved, while favoring data-driven systems offers an opportunity for further investigation, supporting determinism is just as risky. It could inadvertently legitimize a concept that entails serious injustices span to large groups of patients [26, 27].

CONCLUSION

AI has emerged as a transformative force in the landscape of personalized medicine, offering unprecedented opportunities to tailor treatment plans based on individual biological and clinical characteristics. From automating data interpretation and supporting diagnosis to designing patient-specific therapeutic regimens, AI technologies have demonstrated considerable promise in enhancing healthcare outcomes. However, realizing AI's full potential in clinical settings requires overcoming significant hurdles, including issues of data quality, transparency, ethical use, and regulatory compliance. Equally critical is the need for interdisciplinary collaboration among clinicians, data scientists, and policymakers to develop frameworks that ensure the responsible use of AI while maintaining patient trust. As the field progresses, integrating AI with existing medical infrastructure in a way that emphasizes interpretability and inclusivity will be essential to fostering broader adoption and ensuring equitable health benefits for all populations.

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